Predicting Academic Course Preference Using Hadoop Inspired Mapreduce

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Abstract- With the emergence of new technologies, new academic trends introduced into Educational system which results in large data which is unregulated and it is also challenge for students to prefer to those academic courses which are helpful in their industrial training and increases their career prospects. Another challenge is to convert the unregulated data into structured and meaningful information there is need of Data Mining Tools. Hadoop Distributed File System is used to hold large amount of data. The Files are stored in a redundant fashion across multiple machines which ensure their endurance to failure and parallel applications. Knowledge extracted using Map Reduce will be helpful indecision making for students to determine courses chosen for industrial trainings. In this research, we are deriving preferable courses for pursuing training for students based on course combinations. Here, using HDFS, tasks run over Map Reduce and output is obtained after aggregation of results.

Keywords- Distributed File System, data mining, educational data mining, Hadoop, MapReduce.

I. INTRODUCTION

Data mining is one of the most prominent areas in modern technologies for retrieving meaningful information from huge amount of unstructured and distributed data using parallel processing of data. There is huge advantage to Educational sector of following Data Mining Techniques to analyse data input from students, feedbacks, latest academic trends etc which helps in providing quality education and decision-making approach for students to increase their career prospects and right selection of courses for industrial trainings to fulfil the skill gap pertains between primary education and industry hiring students. Data Mining has great impact in academic systems where education is weighed as primary input for societal progress.

Big data is the emerging field of data mining. It is a term for datasets that are so large or complex that traditional data processing application software is incompetent to deal with them. Big data includes gathering of data for storage and analysis purpose which gain control over operations like searching, sharing, visualization of data, query processing, updating and maintain privacy of information. In Big data, here is extremely large dataset that is analysed computationally to reveal patterns, trends and associations. It deals with unstructured data which may include MS Office files, PDF, Text etc whereas structured data may be the relational data.

Hadoop is one technique of big data and answer to problems related to handling of unstructured and massive data. Hadoop is an open-source programming paradigm which performs parallel processing of applications on clusters. Big Data approach can help colleges, institutions, universities to get a comprehensive aspect about the students. It helps in answering questions related to the learning behaviours, better understanding and curriculum trends, and future course selection for students which helps to create captivating learning experiences for students. The problem of enormously large size of dataset can be solved using Map Reduce Techniques. Map Reduce jobs run over Hadoop Clusters by splitting the big data into small chunks and process the data by running it parallel on distributed clusters.

II. LITERATURE REVIEW

Implementation of Hadoop Operations for Big Data Processing in Educational Institutions

Education plays an important role in maintaining the economic growth of a country. The objective of this paper is to focus on the impact of cloud computing on educational institutions by using latest big data technology to provide quality education. Our educational systems have a large amount of data. Big Data is defined as massive sets of data that is so large or so complex that it is very difficult to process by using conventional applications and software technologies. This has resulted in the penetration of Big Data technologies and tools into education, to process the large amount of data involved. In this paper we discuss what Cloud and Hadoop is, and its types, operations and services offered. Hence it has an advantage which will surely help the students when used in an appropriate way. Predicting Student Performance Using Map Reduce Data mining and machine learning depend on classification which is the most essential and important task. Many experiments are performed on Student datasets using multiple classifiers and feature selection techniques. Many of them show good classification accuracy. The existing work proposes to apply data mining techniques to predict Students dropout and failure. But this work doesn't support the huge amount of data. It also takes more time to complete the classification process. So, the time complexity is high. To improve the accuracy and reduce the time complexity, the Map Reduce concept is introduced. In this work, the deadline constraint is also introduced. Based on this, an extensional Map Reduce Task Scheduling algorithm for Deadline constraints (MTSD) is proposed. It allows user to specify a job's (classification process in data mining) deadline and tries to make the job to be finished before the deadline. Finally, the proposed system has higher classification accuracy even in the big data and it also reduced the time complexity.

Map Reduce as a Programming Model for Association Rules Algorithm on Hadoop as association rules widely used, it needs to study many problems, one of which is the generally larger and multi-dimensional datasets, and the rapid growth of the amount of data. Single processor's memory and CPU resources are very limited, which makes the algorithm performance inefficient. Recently the development of network and distributed technology makes cloud computing a reality in the implementation of association rules algorithm. In this paper we describe the improved Apriori algorithm based on Map Reduce mode, which can handle massive datasets with a large number of nodes on Hadoop platform.

Apriori-Map/Reduce Algorithm Map/Reduce algorithm has received highlights as cloud computing services with Hadoop frame works were provided. Thus, there have been many approaches to convert many sequential algorithms to the corresponding Map/Reduce algorithms. The paper presents Map/Reduce algorithm of the legacy Apriori algorithm that has been popular to collect the item sets frequently occurred in order to compose Association Rule in Data Mining. Theoretically, it shows that the proposed algorithm provides high performance computing depending on the number of Map and Reduce nodes.

III. PROPOSED SYSTEM

Using Map Reduce, the application can be scaled to run over multiple machines in a cluster and for that Hadoop cluster is used. The Map Reduce Framework consists of Map and Reduce Functions with single Resource Manager which acts as a master and one Node manager which acts as slave per cluster node. The input dataset is fed into the mapper and after passing through shuffle phase, reducer displays the output after aggregating the tuples obtained from mapper and are in the form of <key, value> pair.

IV. METHODOLOGY

Dataset for Course Selection

Table I shows the list of course combinations taken by students for their industrial trainings

Course Combination	Preferable Course
Java,J2EE	Android
HTML, Javascript	PHP
C,C++ Asp.Net	Asp.Net
J2EE,Java	Android
C,C++	Java

Table I. Dataset for Course Selection

Here each row is considered as transaction, each comprising a combination of variables or item sets. The pattern of student's choice for industrial training course combinations is predicted after processing through MAP Reduce Hadoop Data Mining Technique shown in figure.

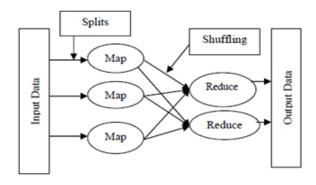


Fig 1: MapReduce Organization Chart

The input dataset collected from students is shown in Table I is stored in the HDFS for MapReduce. The input data is then split into various clusters and provide it to the mapper that maps data to the output. The output from the mapper is represented as <key, value> pair. The output obtained from the mapper are then combined together in the combiner and then sent to the reducer.

Here, for organizing the work, Hadoop divides the task into Map and Reduce Tasks. The components of Hadoop Distributed File System are discussed below. The Map Reduce program transforms lists of input data elements into list of output data elements and it will be done using twice by Map and Reduce. The cluster running applications and name node information in the form of Web Interfaces using Hadoop.

The Organisation Structure of Map Reduce Framework is shown in Fig.1which represents that input data obtained from Table 1 first splits and then mapped followed with shuffling. The unstructured data after shuffling filtered to obtain output which is also called "Reduce Phase".

A. Mapper

In Map function, individual jobs transform records into intermediate records. There is multiplicity in the input pair which map to zero or one to many output pairs.

B. Reducer

In Reducer Function, the set of intermediate value share key of smaller set of values which reduces the overhead of the system. In reducer, output is obtained after merging.

C. Name Node

The Name node is the main feature of Hadoop Distributed File System. The name node stores all the metadata for the file system, using yarn command, the Fig.3 and 4 shows the node manager and resource manager running concurrently. The Name node uses RAM space.

D. Data Node

Data node stores the actual data in HDFS. Here, data node is known as Slave and Name node is known as Master. There is Master-Slave communication between Name node and Data node. When data node starts, it communicates to the Namenode along with blocks list managed by it. The Datanode uses Hard disk space.

E. Resource Manager

The progress of the jobs running in cluster can be viewed through Resource Manager Web interface shown in Fig.6. Along with it, the status of the scheduler can also be viewed. The resource manager determines all the available cluster resources and help in managing the distributed applications. It works with Node Manager and Application Master.

Apache Hadoop Distribution - hadoop namenode	-		\times
2020-04-17 22:44:54,087 INFO namenode.FSDirectory: Initializing quota ((s)	with	4 thr	ead ^
2020-04-17 22:44:54,115 INFO namenode.FSDirectory: Quota initialization n 27 milliseconds name space-1	n com	plete	d i
storage space=0			
storage types=RAM DISK=0, SSD=0, DISK=0, ARCHIVE=0, PROVIDED=0			
2020-04-17 22:44:54,151 INFO blockmanagement.CacheReplicationMonitor: eReplicationMonitor with interval 30000 milliseconds	Start	ing C	ach
2020-04-17 22:44:55,147 INFO hdfs.StateChange: BLOCK* registerDatanode deRegistration(127.0.0.1:9866, datanodeUuid-94e23Sfa-78fd-413e-95e5-5d hfOport-9864, infoSecurePort=0, ipCPort-9867, storageInfo=1v=-57;Cid=C c7b-4208-b192-2e4b6bf8736f;nsid=660255427;c=1587150857190) storage 94e 3e-95e5-5d8d4c52bcaf	84dc6 ID-11	2bcaf d9a06	, i 3-f
2020-04-17 22:44:55,152 INFO net.NetworkTopology: Adding a new node: /d	defau	lt-ra	ck/
127.0.0.1:9866			
2020-04-17 22:44:55,153 INFO blockmanagement.BlockReportLeaseManager: H 94e235fa-78fd-413e-95e5-5d84dc62bcaf (127.0.0.1:9866).	Regis	tered	DN
2020-04-17 22:44:55,353 INFO blockmanagement.DatanodeDescriptor: Adding ID DS-de0ef9eb-f03b-40b4-8bdd-dd36b16ee068 for DN 127.0.0.1:9866	g new	stor	age
2020-04-17 22:44:55,473 INFO BlockStateChange: BLOCK* processReport 0x0 c90: Processing first storage report for D5-de0ef9eb-f03b-40b4-8bdd-dd om datanode 94e235fa-78fd-413e-95e5-5084dc62bcaf			
2020-04-17 22:44:55,478 INFO BlockStateChange: BLOCK* processReport 0x: C00: from storage D5-08004700-f803-0404-8406-d305b160068068 node Datanodd (127.0.0.1:9866, datanodeUuid=94e235fa-78fd-413e-95e5-5d84dc62bcaf, in: InfoSecurePort=0, lpcPort=9867, storageInfo=lv=-57;cid=CID-1149a063-fc7; 24b6bF8756f;ns1d=60255427;c=15871208257109), blocks: 0, hasStaleStora	eRegi foPor 7b-42	strat t=986 08-b1	ion 4, 92-
ocessing time: 5 msecs, invalidatedBlocks: θ			

Fig.2 Hadoop Name Node

F. Job Tracker

Job tracker plays an important role for complete execution of the tasks submitted. Job tracker resides on name node when only one task to be accomplished and for multiple tasks, job tracker resides on Data node. The overall progress of each job is tracked through Job Tracker.

📾 Apache Hadoop Distribution - yam nodemanager 🔍			101	×
Apr 17, 2020 10:47:04 PM com.sun.jersey.guice.sp	i.container.Gui	ceComponent	Provid	lerF
ctory register				
NFO: Registering org.apache.hadoop.yarn.server.	nodemanager.web	app.JAXBCor	itextRe	sol
er as a provider class				
pr 17, 2020 10:47:04 PM com.sun.jersey.server.i initiate				np1
NFO: Initiating Jersey application, version 'Je pr 17, 2020 10:47:04 PM com.sun.jersey.guice.sp ctory getComponentProvider				1erF
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pr 17, 2020 10:47:04 PM com.sun.jersey.guice.sp ctory getComponentProvider	i.container.Gui	ceComponent		lerF
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pr 17, 2020 10:47:06 PM com.sun.jersey.guice.sp ctory getComponentProvider		ceComponent		lerF
NFO: Binding org.apache.hadoop.yarn.server.node eManagedComponentProvider with the scope "Singl		MWebServio		Gui
020-04-17 22:47:06,268 INFO handler.ContextHand 3630939{/,flle:///C:/Users/HFadl/AppData/Local/ 353495797710539143.dir/webapp/.AVAILABLE}//node	ler: Started o. Temp/jetty-0.0.			
020-04-17 22:47:06,284 INFO server.AbstractConn a8{HTTP/1.1,[http/1.1]}{0.0.0.0:8042}		ServerConne	tctor@4	106f
020-04-17 22:47:06.285 INFO server.Server: Star	ted @13636ms			
020-04-17 22:47:06,286 INFO webapp.WebApps: Web		ed at 8042		
020-04-17 22:47:06.289 INFO nodemanager.NodeSta			signed	1 15
: DESKTOP-SSVATPO: 57849				
020-04-17 22:47:06,319 INFO client.RMProxy: Con	necting to Reso	unceManager	at /e	9.0.
020-04-17 22:47:06,327 INFO util.JvmPauseMonito	r: Starting JVM	pause mont	tor	
020-04-17 22:47:06.448 INFO nodemanager.NodeSta	tusUpdaterImpl:	Sending ou	IT O NN	1 co
tainer statuses: []		Bernerig		
020-04-17 22:47:06,476 INFO nodemanager.NodeSta	tusUpdaterImpl:	Registerir	ng with	RM
using containers :[]				
020-04-17 22:47:06,999 INFO security.NMContaine	rTokenSecretMan	ager: Rolli	ng mas	ter
key for container-tokens, got key with id -6115	78912		Co mars	
020-04-17 22:47:07,001 INFO security.NMTokenSec	retManagerInNM:	Rolling ma	ster-k	cev
or container-tokens, got key with id -977682056		- B		
020-04-17 22:47:07,003 INFO nodemanager.NodeSta		Registered	with	Res
urceManager as DESKTOP-SSVATPQ:57849 with total	resource of <m< td=""><td>emory:8192,</td><td>vCore</td><td>25:8</td></m<>	emory:8192,	vCore	25:8

Fig.3 Hadoop Node Manager

📾 Apache Hadoop Distribution - yarn resourcemanager 🔫	
2020-04-17 22:47:05,659 INFO store.AbstractFSNode	
<pre>at:file:/tmp/hadoop-yarn-HFadl/node-attribute/n</pre>	
2020-04-17 22:47:05,695 INFO event.AsyncDispatche	
doop.yarn.server.resourcemanager.nodelabels.NodeA	
org.apache.hadoop.yarn.server.resourcemanager.nod	ielabels.NodeAttributesManagerImpl
ForwardingEventHandler	
2020-04-17 22:47:05,702 INFO placement.MultiNodes	SortingManager: Starting NodeSorti
gService=MultiNodeSortingManager	
2020-04-17 22:47:05,749 INFO ipc.CallQueueManager	.: Using callQueue: class java.uti
.concurrent.LinkedBlockingQueue, queueCapacity: 5	000, scheduler: class org.apache.
adoop.ipc.DefaultRpcScheduler, ipcBackoff: false.	
2020-04-17 22:47:05,765 INFO pb.RpcServerFactoryF	BImpl: Adding protocol org.apache
hadoop, yarn, server, api, ResourceTrackerPB to the s	erver
2020-04-17 22:47:05,799 INFO ipc.Server: Starting	Socket Reader #1 for port 8031
2020-04-17 22:47:05.825 INFO ipc.Server: IPC Serv	ver listener on 8031: starting
2020-04-17 22:47:05,820 INFO ipc.Server: IPC Serv	
2020-04-17 22:47:05.847 INFO util.JvmPauseMonitor	: Starting JVM pause monitor
2020-04-17 22:47:05,853 INFO ipc.CallQueueManager	
.concurrent.LinkedBlockingQueue, queueCapacity: 5	000, scheduler: class org.apache.
adoop.ipc.DefaultRpcScheduler. ipcBackoff: false.	
2020-04-17 22:47:05,929 INFO ipc.Server: Starting	
2020-04-17 22:47:05,956 INFO pb.RpcServerFactory	BImpl: Adding protocol org.apache
hadoop.yarn.api.ApplicationMasterProtocolPB to th	
2020-04-17 22:47:06,007 INFO ipc.Server: IPC Serv	ver listener on 8030: starting
2020-04-17 22:47:06,008 INFO ipc.Server: IPC Serv	ver Responder: starting
2020-04-17 22:47:06,263 INFO ipc.CallQueueManager	: Using callQueue: class java.uti
.concurrent.LinkedBlockingOueue, gueueCapacity: 5	000. scheduler: class org.apache.
adoop.ipc.DefaultRpcScheduler, ipcBackoff: false.	
2020-04-17 22:47:06,288 INFO ipc.Server: Starting	Socket Reader #1 for port 8032
2020-04-17 22:47:06,298 INFO pb.RpcServerFactoryF	
hadoop.yarn.api.ApplicationClientProtocolPB to th	ie server
2020-04-17 22:47:06,320 INFO resourcemanager.Reso	ourceManager: Transitioned to act:
e state	
2020-04-17 22:47:06,331 INFO ipc.Server: IPC Serv	
2020-04-17 22:47:06,333 INFO ipc.Server: IPC Serv	
2020-04-17 22:47:06,961 INFO resourcemanager.Reso	
om node DESKTOP-SSVATPQ(cmPort: 57849 httpPort: 8	
memory:8192, vCores:8>, assigned nodeId DESKTOP-5	SVATPQ: 57849
2020-04-17 22:47:06,970 INFO rmnode.RMNodeImpl: D	DESKTOP-SSVATPQ:57849 Node Transit
oned from NEW to RUNNING	
2020-04-17 22:47:07,016 INFO capacity.CapacitySch	neduler: Added node DESKTOP-SSVATE
:57849 clusterResource: <memory:8192, vcores:8=""></memory:8192,>	

Fig.4 Yarn Resource Manager

Hadoop Overview Datanodes Datanode Volume F	alures Srapshot	Sartup Progress	Unites		
NameNode is still loading. Redirecting to the Startup Progress	i page				
Startup Progress					
Elapsed Time: 0 sec, Percent Complete: 0%					
Phase		Completion		Elapsed Time	
Loading fsimage		0%		0 sec	
Loading edits		0%		0 sec	
Saving checkpoint		0%		0 sec	
Sale mode		2%		0 sec	
Hadoop, 2015.					

Fig.5 Web Interface of Name Node

The features and attributes shown in Figure 5 and 6 are tabulated in Table II. In Table Cluster Metrics and Scheduler Metrics are shown with Memory Consumption and Hadoop Distributed File System Health.



Fig.6 Web Interface of Resource Manager displaying Cluster Information

V. RESULT & FUTURE SCOPE

After processing the input data through Map Reduce in Hadoop, display the desired output. The input dataset splits and after mapping, process of shuffling is performed and the output of Mapper becomes input to Reducer function and after this final output is obtained. The result shows that maximum of students have shown key interest towards "C, C++ and Java Courses" which not only helps management as well Faculty members for more focus on above mentioned courses.

VI. CONCLUSION

The Map Reduce approach is used for running jobs over HDFS. Using Map Reduce, the application can be scaled to run over multiple machines in a cluster and for that Hadoop cluster is used. The Map Reduce Framework consists of Map and Reduce Functions with single Resource Manager which acts as a master and one Node manager which acts as slave per cluster node. The input dataset is fed into the mapper and after passing through shuffle phase, reducer displays the output after aggregating the tuples obtained from mapper and are in the form of <key, value> pair.

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 "Implementation of Hadoop Operations for Big Data Processing in Educational Institutions", International Journal of Innovative Research in Computer and Communication Engineering, ISSN(Online) : 2320-9801, Vol. 4, Issue 4, April 2016.
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